AUTOMATIC LESION DETECTION OF DIABETIC RETINOPATHY FROM COLOR RETINAL PHOTOGRAPHS

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Abstract

Automatic detection of microaneurysms in digital color fundus images is still an open issue in medical image processing. In this paper, it propose a method to improve microaneurysm detection. Unlike the well-known approach of considering the output of multiple classifiers, it propose a combination of internal components of microaneurysm detectors such as preprocessing methods and candidate extractors. Since microaneurysm detection is decisive in diabetic retinopathy (DR) grading, also tested the proposed method for this task on the publicly available Messidor database, where a promising result is achieved in a "DR/non-DR"-type classification based on the presence or absence of the microaneurysms.

Index Terms— Diabetic retinopathy (DR) grading, Color fundus image processing, microaneurysm (MA) detection.

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I. INTRODUCTION

DIABETIC retinopathy (DR) is the result of micro vascular retinal changes triggered by diabetes that can lead to complete loss of sight if not treated in a timely manner. Recent reports have shown that approximately 25 000 people with diabetes go blind every year in the U.S. due to DR [1]. According to [1], in the U.S. and Europe, DR is the major cause of blindness for the economically active population and, according to [2], is estimated that DR is responsible for 5% of all the world's blindness cases. DR is a serious eye disease that originates from diabetes mellitus and is the most common cause of blindness in the every country. Early treatment can prevent patients to become affected from this condition or at least the progression of DR can be slowed down. Thus, mass screening of patients suffering from diabetes is highly desired, but manual grading is slow and resource demanding.

A key feature to recognize DR is to detect microaneurysms (MAs) in the fundus of the eye. MAs are the swellings of the capillaries formed by the weakening of the vessel wall. The importance of handling MAs are twofold. First, they are normally the earliest signs of DR, hence their timely and precise detection is essential. On the other hand, the grading performance of computer-aided DR screening systems highly depends on MA detection [3], [4]. In this paper, we propose a MA detector that provides remarkable results from both aspects.

One way to ensure high reliability and raise accuracy in a detector is to consider ensemble-based systems, which have been proven to be efficient in several fields. However, the usual ensemble techniques aim to combine class labels or real values that cannot be adopted in our case. In MA detection, detectors provide spatial coordinates as centers of potential MA candidates. The use of well-known ensemble techniques would require a classification of each pixel, which can be misleading in our context, since different algorithms extract MAs with different approaches and the MA centers may not coincide exactly. To overcome this difficulty, we gather close MA candidates of the individual detectors and apply a voting scheme on them.

In [5], Niemeijer et al. showed that the fusion of the results of the several MA detectors leads to an increased average sensitivity measured at seven predefined false positive rates. In this

paper, we propose a framework to build MA detector ensembles based on the combination of the internal components of the detectors not only on their output as in [5]. Some of earlier research on combining MA detectors did not provide reassuring results [6]. To increase the accuracy of such ensembles, it must identify the weak points of MA detection. The first difficulty originates from the shape characteristics of MAs. They appear as small circular dark spots on the surface of the retina, which can be hard to distinguish from fragments of the vascular system or from certain eye features. Most MA detectors tackle this problem in the following way: first, the green channel of the fundus image is extracted and preprocessed to enhance MA like characteristics. Then, in a coarse level step all MA-like objects are detected in the image. Finally, a fine level algorithm removes the potentially false detections based on some assumptions about it.

The former investigations showed that the low sensitivity of MA detectors originates from the candidate extractor part [7]. However, we could increase the sensitivity by applying proper preprocessing methods before candidate extraction. This technique causes a slight increment in the number of false positives, but it can be decreased by classification or voting. In this paper, it propose an effective MA detector based on the combination of preprocessing methods and candidate extractors. It provide an ensemble creation framework to select the best combination. An exhaustive quantitative analysis is also given to prove the superiority of our approach over individual algorithms.

It also investigate the grading performance of its method, which is proven to be competitive with other screening systems. The rest of the paper is organized as follows: the selected preprocessing methods and candidate extractors are presented in Sections II and III, respectively. The proposed candidate extraction method is explained in the section IV.The methodology

II. PREPROCESSING METHODS

In this section, we present the selected preprocessing methods, which we consider to be applied before executing MA candidate extraction. The selection of the preprocessing method and candidate extractor components for this framework is a challenging task. Since preprocessing methods need to be highly interchangeable, we must select algorithms that can be

used before any candidate extractor and do not change the characteristics of the original images (unlike e.g., shade correction [8]). We also found some techniques to generate too noisy images for MA detection (histogram equalization [8], adaptive histogram equalization [8] or color normalization [8]). Thus, we have selected methods which are well-known in medical image processing and preserve image

characteristics. Naturally, the proposed system can be improved in the future with adding new methods. A comparative study of various preprocessing methods dedicated to lesion detection are discussed below.

A. Contrast Enhancement method [9]

This preprocessing method aims to enhance the contrast of fundus images by applying a gray level transformation using the following operator:

$$f' = \begin{cases} \dfrac{\frac{1}{2}(f'_{\max} - f'_{\min})}{(\mu - f_{\min})^r} \cdot (f - f_{\min})^r + f'_{\min}, & f \le \mu \\ -\dfrac{\frac{1}{2}(f'_{\max} - f'_{\min})}{(\mu - f_{\max})^r} \cdot (f - f_{\max})^r + f'_{\max}, & f \ge \mu \end{cases}$$

where {fmin, . . . , fmax}, {f'min, . . . , f'max} are the intensity levels of the original and the enhanced image, respectively, ì is the mean value of the original grayscale image and r ∈ R is a transition parameter.

B. Contrast Limited Adaptive Histogram Equalization [10]

Contrast limited adaptive histogram equalization (CLAHE) is a popular technique in biomedical image processing, since it is very effective in making the usually interesting salient parts more visible. The image is split into disjoint regions, and in each region local histogram equalization is applied. Then, the boundaries between the regions are eliminated with a bilinear interpolation.

C. Illumination Equalization [8]

This preprocessing method aims to reduce the vignetting effect caused by uneven illumination of retinal images. Each pixel intensity is set according to the following formula:

$$f' = f + \mu_d - \mu_l$$

where f, f' are the original and the new pixel intensity values, respectively, μ_d is the desired average intensity, and μ_l is the local average intensity. MAs appearing on the border of the retina are enhanced by this step.

III. MA CANDIDATE EXTRACTORS

Candidate extraction is a process that is used to spot any objects in the image showing any lesions present in it. Individual MA detectors consider different principles to extract MA candidates. In this section, we provide a brief overview of the candidate extractors involved in our analysis. Again, just as for preprocessing methods, adding new MA candidate extractors may lead to further improvement in the future.

A. Walter et al. [14]

Candidate extraction is accomplished by grayscale diameter closing. That is, this method aims to find all sufficiently small dark patterns on the green channel. Finally, a double threshold is applied.

B. Circular Hough-Transformation [17]

Following the idea presented in [17], we established an approach based on the detection of small circular spots in the

image. Candidates are obtained by detecting circles on the images using circular Hough transformation. With this technique, a set of circular objects can be extracted from the image.

C. Zhang et al. [18]

In order to extract candidates, this method constructs a maximal correlation response image for the input retinal image. This is accomplished by considering the maximal correlation coefficient with five Gaussian masks with different standard deviations for each pixel. The maximal correlation response image is thresholded with a fixed threshold value to obtain the candidates. Vessel detection and region growing is applied to reduce the number of candidates, and to determine their precise size, respectively.

D. Lazar et al. [19]

Pixel-wise cross-sectional profiles with multiple orientations are used to construct a multidirectional height map. This map assigns a set of height values that describe the distinction of the pixel from its surroundings in a particular direction. In a modified multilevel attribute opening step, a scoremap is constructed from which the MAs are extracted by thresholding.

IV.PROPOSED CANDIDATE EXTRACTION METHOD

From the input fundus image, the vascular map is extracted by applying 12 morphological black top-hat transformations with 12 rotated linear structuring elements. Then, the vascular map is subtracted from the input retinal image, which is followed by the fourier transform of the image and application of a Gaussian matched filter. The resulting image is then binarized with a fixed double threshold. Since the extracted candidates are not precise representations of the actual lesions, a retinal region growing step is also applied to it.

V. METHODOLOGY

We have evaluated the proposed approach for both MA detection and DR grading. In this section, we present the evaluation methodology we used in each case.

A. MA Detection

We have evaluated the MA detection capabilities of the proposed method in the ROC competition for MA detectors [13], as well as on a publicly available [21] and a private database. In this section, we provide a brief overview on these databases and on the methodology we used for the evaluation of MA detection performance of the proposed approach.

Candidate Retinal Region Growing

Region growing was performed at each candidate MA using pixel as a seed. Given a threshold value t>0, C(t) is defined as the largest 8-connected region which contains q and in which $S(P) \leq S(q) + t$, for all P in C(t) . These regions were evaluated for t=0.1, 0.2, …t_{max} where t_{max} is the largest value in this sequence for which area C(t)<3000 pixels. Now an "energy" function is defined as the mean squared gradient magnitude of S around the boundary of C(t) using

$$G = \mathrm{grad}(S)^2$$
$$E(t) = \mathrm{mean}_{p \in \mathrm{boundary}(C(t))} G(p).$$

Then a fourier transform operation on the resultant image is performed and finally a double threshold is applied to the resultant image, we gets the MA candidates clearly.

B. DR Grading

We have also evaluated our approach to see its grading performance to recognize DR. For this aim, we determined the image-level classification rate of the ensemble on the Messidor dataset containing 1200 images. That is, the presence of any MA means that the image contains signs of DR, while the absence of MAs indicates a healthy case. In other words, a pure yes/no decision of the system has been tested. For each image, a grading score ranging from R0 to R3 is provided. These grades correspond to the following clinical conditions: a patient with an R0 grade has no DR. R1 and R2 are mild and severe cases of nonproliferative retinopathy, respectively. Finally, R3 is the most serious condition (proliferative retinopathy). The grading is based on the appearance of MAs, haemorrhages and neovascularization. In our evaluation, we classified the retinal images whether they contain signs of DR (R1, R2, R3) or not (R0). The MA detector classifies an image as diseased if at least one MA was detected and healthy otherwise.

VI. DISCUSSION

A strong point of the proposed method is that it performs well under difficult circumstances. In the preprocessing method of the image to CLAHE made it easier to distinguish the MAs from their background. However, the use of the vessel removal and inpainting preprocessing method caused the missing of a true MA, while the detection of the remaining MA is easier in the absence of thin retinal vessels. Thus, using different preprocessing methods with candidate extractors creates diversity among the members of the ensemble, which is desired for systems

using multiple estimators [24]. This diversity ensures the suppression of false detections, since diverse detectors tend to make different mistakes. Thus, the false detections are likely to receive lower confidence values in the voting procedure.

Our experimental results show that the proposed MA detector outperforms the current individual approaches in MA detection. It has been also proven that the framework has high flexibility for different datasets. As can be seen, the ensemble members may vary, which suggests relatively high variance among databases in this field. Thus, we can recommend to use an affordable level for thresholding at the extraction phase and use it for detecting MAs on unknown images.

Despite the promising results, the system still misclassifies some stage, where serious case of DR is present. To improve grading performance, we must take into account the presence or absence of more DR-specific lesions (e.g., exudates), image quality, the recognition of anatomical parts which are essential in a clinical setting. However, our MA detector can serve as a main component of such a system.

VII. CONCLUSION

In this paper, we have proposed a MA detector method that has proved its high efficiency in the various tests conducted. Our framework relies on a set of preprocessing method, candidate extractor method pairs, from which a search algorithm selects an optimal combination. Since our approach is modular, we can expect further improvements by adding more preprocessing methods and candidate extractors. The grading results presented in this paper are already promising. However, a proper screening system should contain other components, which is expected to increase the performance of this approach, as well.

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